In Large Language Models (LLMs), changing sampling temperature does not affect performance on problem-solving tasks*.



Question

What is the optimal sampling temperature for LLM performance on problem-solving tasks?

Experiment

To measure the effect of sampling temperature on problem solving, we used 9 LLMs, with 5 prompts, to solve 1,000 problems, from 10 exams, 10 times each, across temperatures of 0.0 to 2.0 in increments of 0.1.





Accuracy by temperature from 0.0 to 1.6 for GPT-3.5 using CoT prompt on the 100-question examination examined and the second sec

Results

Models

Name	Vendor
Claude 3 Opus	Anthropic
Command R+	Cohere
Gemini 1.0 Pro	Google
Gemini 1.5 Pro	Google
GPT-3.5 Turbo	OpenAl
GPT-4	OpenAl
Llama 2 7B	Meta
Llama 2 70B	Meta
Mistral Large	Mistral AI

Problem Sets Benchmark Name Arc Challenge ARC AQUA-RAT AGI Eval Hellaswag HellaSwag LogiQA AGI Eval LSAT-AR AGI Eval LSAT-LR AGI Eval LSAT-RC AGI Eval MedMCQA MedMCQA

More Results



Accuracy by temperature and model using the CoT prompt on the 100-question exam.





using the CoT prompt.



SAT-English	AGI Eval
SAT-Math	AGI Eval

Temperature

Accuracy by temperature and prompt for GPT-3.5 using the CoT prompt on the 100-question exam.

Temperature Text similarity by temperature for GPT-3.5 using the CoT prompt on the 100-question exam.

Prompts

Baseline – no prompt engineering (used as a baseline) **Domain Expertise** – specifies the LLM is an expert in the problem domain **Self-recitation** – instructs the LLM to recite its own internal knowledge first **Chain of Thought** – instructs the LMM to "think step-by-step" **Composite** – combines all three prompts and adds self-criticism

Conclusion

Changes to sampling temperature from 0.0 to 1.0 have no statistically significant effects on problem-solving for multiple-choice question-answer (MCQA) problems.

The Effect of Sampling Temperature on Problem Solving in Large Language Models Matthew Renze and Erhan Guven Johns Hopkins University

